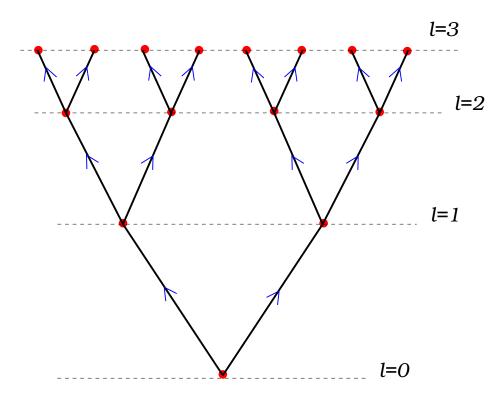
# Information broadcast on a tree and reconstruction

Marc Mézard, joint work with Andrea Montanari

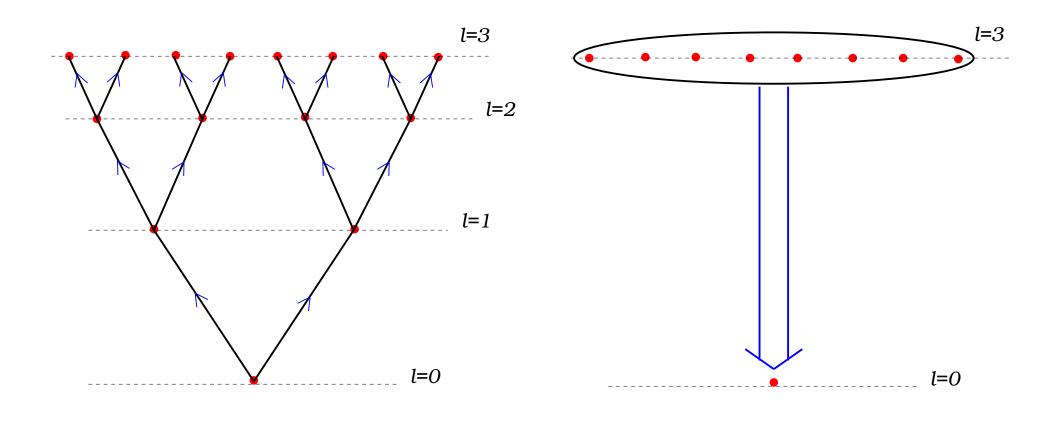
Santa Fe, may 2007

# The broadcast/reconstruction problem



Broadcast on a tree

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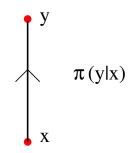
Reconstruction

#### **Motivation**

- Communication network
- Propagation of genetic information
- Generalization of Markov chain to trees
- Statistical physics on a Cayley tree / Bethe lattice
- Optimization problems and error correcting codes: locally tree-like networks
- Spin glass phase

#### **Communication channel**

Message from alphabet, e.g.  $x, y \in \{1, \dots, q\}$ Broadcast  $x \to y$ : probability  $\pi(y|x)$ .

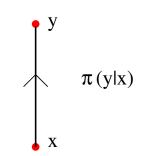


#### Example "Ferromagnetic Potts channel":

$$\pi(y|x) = \begin{cases} 1 - \varepsilon & \text{if } y = x \\ \frac{\varepsilon}{q-1} < 1 - \varepsilon & \text{otherwise} \end{cases}$$

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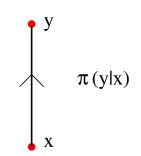
$$\pi(y|x) = \begin{cases} 1 - \varepsilon & \text{if } y = x \\ \frac{\varepsilon}{q - 1} < 1 - \varepsilon & \text{otherwise} \end{cases} = \frac{1}{q - 1 + e^{\beta}} \exp(\beta \delta_{x, y})$$

Noise level in the channel:  $T=1/\beta$  (related to  $\varepsilon$  by  $e^{-\beta}=\frac{\varepsilon}{(q-1)(1-\varepsilon)}$ )

 $\varepsilon \in [0, \frac{q-1}{q}]$ ; Larger  $\varepsilon \to \mathsf{Higher}$  temperature.

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('Antiferromagnetic' channel:  $\varepsilon \in [\frac{q-1}{q}, 1]$ .  $\varepsilon = 1 \rightarrow \text{proper coloring}$ )

# Information on the boundary about the root

Broadcast: generates a boundary configuration B.

Reconstruction: Does B contain some information on the letter sent from the root, in the large  $\ell$  limit?

Potts channel broadcasted from  $x_0 = 1$ :

$$\psi_{\ell} = \sum_{B} P_{broadcast}(B|x_0 = 1)P(x = 1|B) - \frac{1}{q}.$$

Reconstruction possible iff  $\lim_{\ell\to\infty}\psi_{\ell}>0$ .

Phase transition (Mossel):

Rec. possible for  $\varepsilon < \varepsilon_r$  (i.e.  $T < T_r$ ), impossible for  $\varepsilon > \varepsilon_r$ 

#### Reconstruction versus "census reconstruction"

- Single variable on the boundary: correlation with root decays as  $e^{-c\ell}$  when  $\ell \to \infty$ , as soon as  $\beta < \infty$ .
- Census reconstruction: information contained in the number of boundary sites with x=1?
- Reconstruction: information contained in the full boundary pattern?

## A simple upper bound: ferromagnetic transition

Fully polarized boundary, x = 1 on all sites.

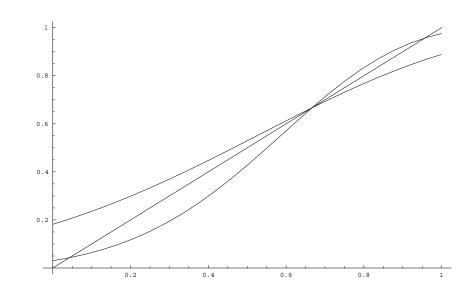
Reconstruction. Shell n: probability  $\eta^{(n)}(x) = (1-a_n)\delta_{x,1} + \frac{a_n}{q-1}(1-\delta_{x,1})$ .

Mapping:  $a_{n-1} = F(a_n)$ 

Boundary condition  $a_{\ell} = 0$ .

Fixed point  $a = \frac{q-1}{q}$ .

Attractive iff  $\varepsilon > \varepsilon_F = \frac{q}{q-1} \, \frac{k-1}{k}$ 



If  $T > T_F$  no correlation of center with B  $\rightarrow$  reconstruction impossible

Shell n:  $k^n$  variables. Assume  $x_n$   $k^n$  are in state x = 1.

$$x_{n+1} k^{n+1} = \sum_{i=1}^{x_n} \frac{k^{n+1}}{u_i} + \sum_{j=1}^{(1-x_n)} \frac{k^{n+1}}{z_j}$$

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**Large**  $n: P(x_n) \sim \text{Gaussian}$ 

$$\mathbb{E}(x_n) \sim \frac{1}{q} + C \left| 1 - \varepsilon \frac{q}{q-1} \right|^n$$

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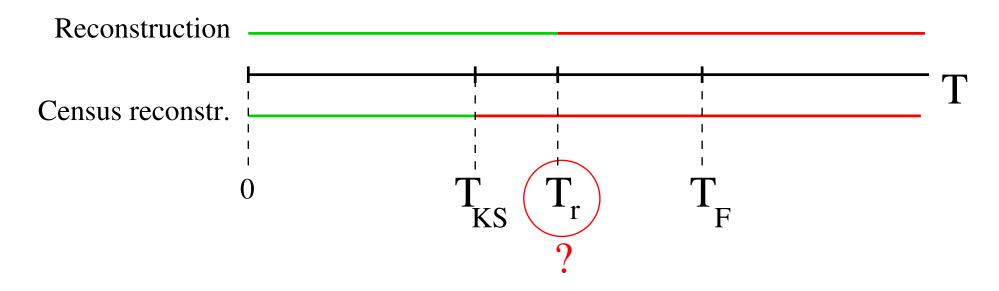
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ightarrow Census reconstruction possible if  $\varepsilon < \varepsilon_{KS} = \frac{q-1}{q} \frac{\sqrt{k}-1}{\sqrt{k}}$ 

Th (Mossel Peres): Threshold for census reconstruction is  $\varepsilon_{KS}$ 

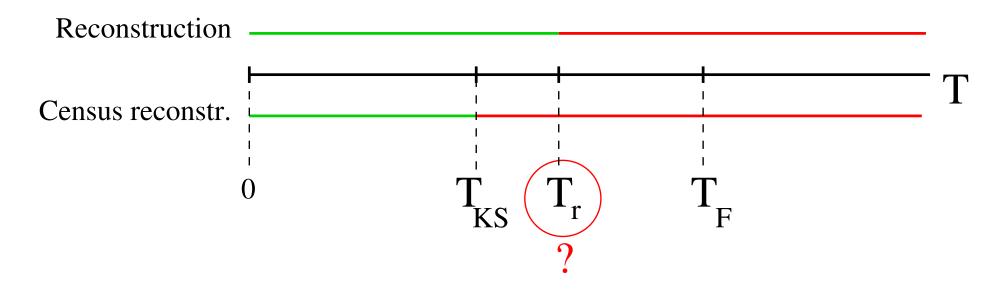
## Some known results on the threshold $T_r$



$$T_{KS}$$
 given by:  $k\left|\lambda_2(\pi)\right|^2=1$ ,  $T_F$  given by:  $k\left|\lambda_2(\pi)\right|=1$ 

$$T_{KS} \le T_r \le T_F$$

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$$T_{KS} \le T_r \le T_F$$

For 
$$q=2$$
:  $T_r=T_{KS}$  (Bleher et al 95)

For q large enough:  $T_r > T_{KS}$  (Mossel Peres 02)

# New results (any tree, any channel)

- Reconstruction threshold  $T_r$  coincides with the dynamical (replica symmetry breaking) spin glass transition for an associated statistical physics problem
- Numerical procedure  $\rightarrow$  locate  $T_r$  with good precision
- Variational principle  $\rightarrow$  new rigorous bounds on  $T_r$  (proven for antiferromagnetic -or in general 'frustrated'- channels)

## **New results: examples**

#### Ferromagnetic Potts

Numerically:  $T_r = T_{KS}$  for q = 3, 4 and  $k \in [2, 30]$ 

$$T_r > T_{KS}$$
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Antiferromagnetic Potts (coloring)

Numerically: Reconstruction in the noiseless limit (proper coloring) is possible only if  $k \ge k_*(q)$ , with  $k_*(3) = 5$ ,  $k_*(4) = 8$ ,  $k_*(5) = 13,...$ 

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$$T_r = T_{KS}$$
 for  $q = 3$  and  $k \in [5, 20]$ 

$$T_r > T_{KS}$$
 for  $q \ge 4$ ,  $k \ge k_*(q)$ .

Rigorous:  $k_*(4) \le 8$ ,  $k_*(5) \le 13$ . Discontinuous transition  $(T_r > T_{KS})$  for q = 4,  $k \in [9, 15]$ , for q = 5,  $k \in [13, 20]$ , for q = 6, k = 20.

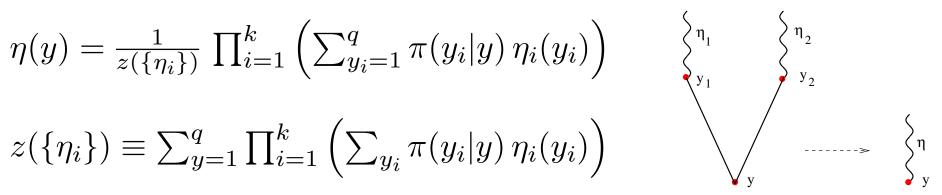
## Reconstruction from a given boundary: recursion

#### Given a boundary:

$$\eta(y) = \frac{1}{z(\{\eta_i\})} \prod_{i=1}^k \left( \sum_{y_i=1}^q \pi(y_i|y) \, \eta_i(y_i) \right)$$

$$z(\lbrace \eta_i \rbrace) \equiv \sum_{y=1}^{q} \prod_{i=1}^{k} \left( \sum_{y_i} \pi(y_i|y) \, \eta_i(y_i) \right)$$

Mapping  $\eta = \mathsf{F}(\eta_1, \dots, \eta_k)$ 

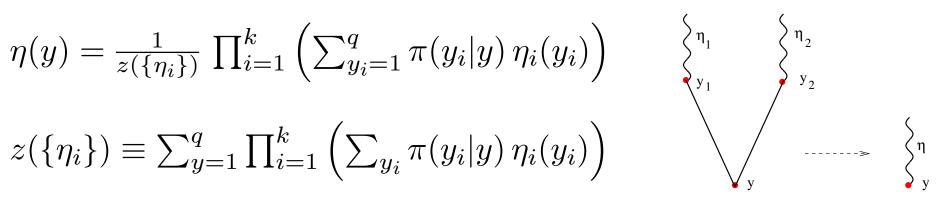


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Mapping 
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Boundary B fixed by broadcast:  $\eta_i(y_i) = \delta_{y_i, y_i^B}$  when i is a leaf.

Iterate from boundary to the center.

#### **Statistics on the boundaries**

For a given boundary B, on each site i of the tree, probability  $\eta_i^B$ , obtained by iteration from boundary to center.

NB: Link to Potts partition function  $Z(y,B) = \sum_{\{y_i\}} \prod_{(ij)\in E} \pi(y_i,y_j)$ :

Broadcast:  $P_{broadcast}(B|y) = Z(y, B)$ 

Reconstruction:  $\eta_i^B(y) = \frac{Z(y,B)}{\sum_{y'} Z(y',B)}$ 

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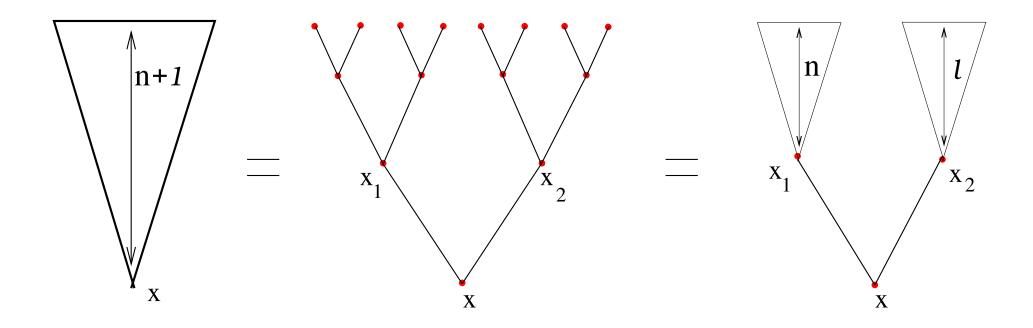
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When B is generated randomly from broadcast (starting from a root fixed to  $x_0$ )  $\to$  probability distribution  $Q_{x_0}(\eta)$  of  $\eta$  on the root.

$$Q_{x_0}(\eta) = \sum_{B} Z(x_0, B) \prod_{x} \delta\left(\eta(x) - \frac{Z(x, B)}{\sum_{x'} Z(x', B)}\right)$$

#### **Functional recursion**



$$Q_x^{(n+1)}(\eta) = \sum_{x_1...x_k} \prod_{i=1}^k \pi(x_i|x) \int \delta \left[ \eta - \mathsf{F}(\eta_1, \dots, \eta_k) \right] \prod_{i=1}^k Q_{x_i}^{(n)}(\eta_i) d[\eta_i]$$

Symmetry property:  $Q_x^{(n)}(\eta)=q\;\eta(x)\;\widehat{Q}^{(n)}(\eta)$  and  $\widehat{Q}^{(n)}(\eta^\sigma)=\widehat{Q}^{(n)}(\eta)$ 

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$$\widehat{Q}^{(n+1)}(\eta) = q^{k-1} \int z(\{\eta_i\}) \delta[\eta - \mathsf{F}(\eta_1, \dots, \eta_k)] \prod_{i=1}^k \widehat{Q}^{(n)}(\eta_i) d[\eta_i]$$

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Fixed point:

$$\widehat{Q}^*(\eta) = q^{k-1} \int z(\{\eta_i\}) \delta[\eta - \mathsf{F}(\eta_1, \dots, \eta_k)] \prod_{i=1}^k \widehat{Q}^*(\eta_i) d[\eta_i]$$

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Spin glass phase ("1-RSB"): exists iff there is a non-trivial symmetric fixed point.

Th: Reconstruction is possible iff there is a spin glass solution  $\widehat{Q}^*$ 

## **Numerical approach**

To obtain  $T_r$ : Solve the fixed point equation

$$\widehat{Q}^*(\eta) = q^{k-1} \int z(\{\eta_i\}) \delta[\eta - \mathsf{F}(\eta_1, \dots, \eta_k)] \prod_{i=1}^k \widehat{Q}^*(\eta_i) d[\eta_i]$$

by a 'population dynamics' ( $\sim$  Monte Carlo) method.

Results

## Variational principle

"Complexity" of a distribution  $\widehat{Q}$ :

$$\Sigma(\widehat{Q}) = \frac{k+1}{2} \int \widehat{W}_{e}(\eta_{1}, \eta_{2}) d\eta_{1} \widehat{Q}(\eta_{1}) d\eta_{2} \widehat{Q}(\eta_{2})$$
$$- \int \widehat{W}_{v}(\eta_{1}, \dots, \eta_{k+1}) \prod_{i=1}^{k+1} d\eta_{i} \widehat{Q}(\eta_{i})$$

where  $\widehat{W}_{\mathrm{e}}$  and  $\widehat{W}_{\mathrm{v}}$  are known...

Theorem: A fixed point  $\widehat{Q}^*$  is a stationary point of  $\Sigma(\widehat{Q})$ .

Conjecture: If there exists a symmetric distribution  $\widehat{Q}$  such that  $\Sigma(\widehat{Q}) > 0$ , then the reconstruction problem is solvable.

Theorem: In the antiferromagnetic channel, if there exists a symmetric distribution  $\widehat{Q}$  such that  $\Sigma(\widehat{Q})>0$ , then the reconstruction problem is solvable.

## Practical use of the variational principle

Compute  $\Sigma$  within some restricted subspace. Define e.g.  $\widehat{Q}_{\mu}$  which attributes equal weight 1/q to the q points  $\eta = \gamma^{(x)}$ ,  $x \in \{1, \ldots, q\}$ :

$$\gamma^{(x)}(y) = \left\{ \begin{array}{ll} 1 - \mu & \text{if } y = x, \\ \mu/(q-1) & \text{otherwise.} \end{array} \right. \text{ and } \Sigma(\mu) = \Sigma(\widehat{Q}_{\mu}).$$

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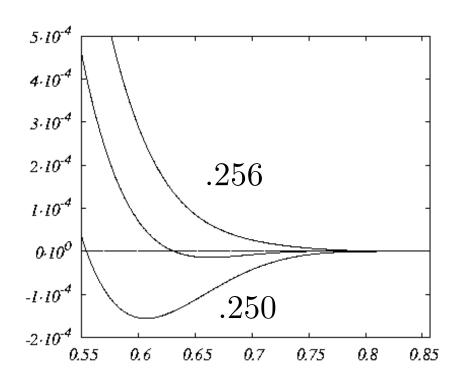
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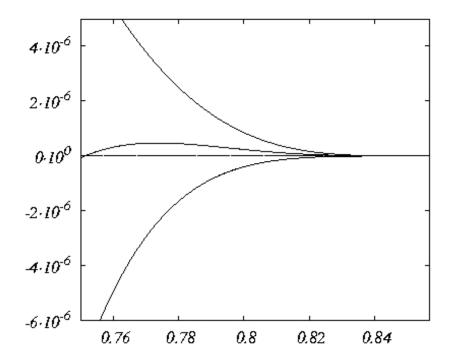
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SG

Example: ferromagnetic Potts, k = 2, q = 7

#### Ferromagnetic Potts, $k=2,\ q=7$ : plot of $-\Sigma$ vs $\mu$ :





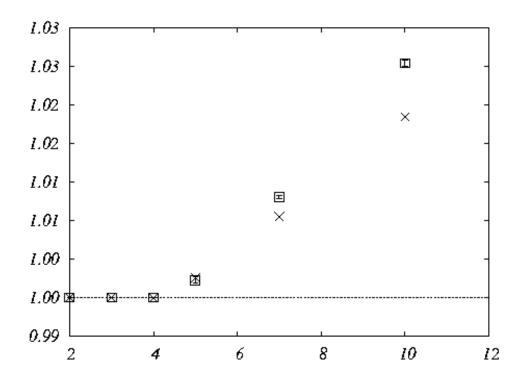
$$k = 2, q = 7. \varepsilon = 0.250, 0.253, 0.256.$$

First order transition:  $\varepsilon_{\rm KS}$  found by  $\frac{d\Sigma}{d\mu}(\mu=(q-1)/q)=0$ 

$$\varepsilon_{\mathrm{KS}} = 0.2510513..; \ \varepsilon_{\mathrm{Var}} = .25369...; \ \varepsilon_r \simeq .25432$$

# Results for the ferromagnetic Potts channel

 $\varepsilon_{\mathrm{r}}/\varepsilon_{\mathrm{KS}}$  as a function of q, for k=2



Squares:  $\varepsilon_{\rm r}(k,q)$ . Crosses: variational lower bound.

Broadcast: generates an equilibrium configuration of the Potts model with free boundary conditions.

Reconstruction: given the boundary B obtained from the broadcast, the conditional probability of the variable on the root, P(x|B), is also given by Boltzmann's measure for the Potts model. But B creates some frustration

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Spin glass on a tree: frustration only through boundary conditions.

Simple Ising spin glass model (Chayes, Chayes, Sethna, Thouless 1986): fix each spin on the boundary to  $\pm 1$  with probability 1/2. But no RSB, no real spin glass phase.

Other boundary condition:  $\prod_{i \in \{ \text{ leaves} \}} \eta_i(x_i)$ , but with correlated  $\eta_i$ :

$$\mathbb{P}(\{\eta_i\}) = \frac{1}{\Xi_L} Z_L(\{\eta_i\}) \prod_{i \in \mathsf{leaves}} \widetilde{Q}^{(0)}(\eta_i) ,$$

where  $\widetilde{Q}^{(0)}(\eta)$  is the uniform distribution on the q 'corners' of the simplex  $\eta(x)=\delta_{x,r}, \quad r\in\{1,\ldots,q\}$ 

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→ functional recursion: identical to the one found in reconstruction

If  $\widetilde{Q}^{(0)} = \widehat{Q}^*$ , this model is statistically invariant by translation (provided rooted tree  $\to$  regular Cayley tree): The properties of a spin don't depend on its shell.

#### Spin glass theory: Bethe lattice

Traditionally, "Bethe lattice" = interior of a Cayley tree

Frustrated systems: frustration from the boundary  $\rightarrow$  bad definition.

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Frustrated systems: frustration from the boundary  $\rightarrow$  bad definition.

Better definition (M+Parisi 2001): use a random regular graph with fixed degree k+1 on each vertex.

Local structure (from a generic point, to any finite depth) = tree.

Frustration from long loops (size of  $O(\log N)$ ).

This work:  $\rightarrow$  Typical boundary condition from outside the tree = the one obtained by broadcast !

## **Cavity method**

Analysis of Potts model on a random regular graph: cavity method  $\rightarrow$  iterative functional equations.

 $\eta_{i\to j}(x_i)=$  marginal distribution of  $x_i$  when the edge i-j has been cut = function of the distributions  $\eta_{l\to i}(x_l)$  where l are the neighbors of i different from j.

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'Liquid' or 'paramagnetic' solution, uniform:  $\eta_{i \to j}(x_i) = \eta(x_i)$ 

Spin glass: many modulated solutions:  $\eta_{i\to j}^\alpha(x_i)$ . Functional  $\widehat{Q}^*(\eta)=$  probability that  $\eta_{i\to j}^\alpha=\eta$ , when  $\alpha$  is chosen randomly with its Boltzmann weight.  $e^{N\Sigma}$  is the number of modulated solutions (BP fixed points)

#### **Cavity method**

Analysis of Potts model on a random regular graph: cavity method  $\rightarrow$  iterative functional equations.

 $\eta_{i\to j}(x_i)=$  marginal distribution of  $x_i$  when the edge i-j has been cut = function of the distributions  $\eta_{l\to i}(x_l)$  where l are the neighbors of i different from j.

'Liquid' or 'paramagnetic' solution, uniform:  $\eta_{i \to j}(x_i) = \eta(x_i)$ 

Spin glass: many modulated solutions:  $\eta_{i \to j}^{\alpha}(x_i)$ . Functional  $\widehat{Q}^*(\eta)$ = probability that  $\eta_{i \to j}^{\alpha} = \eta$ , when  $\alpha$  is chosen randomly with its Boltzmann weight.  $e^{N\Sigma}$  is the number of modulated solutions (BP fixed points)

(NB: spin glass phase may be hidden by a ferromagnetic state, if it exists)

#### **Comments**

A very interesting problem!

Deep connexions to spin glasses

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Several open questions: prove variational conjecture also in unfrustrated cases  $\rightarrow$  best known bounds... Meaning of the complexity directly in the broadcast/reconstruction problem?

#### **Comments**

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Ref: "Reconstruction on trees and spin glass transition", Marc Mézard and Andrea Montanari, J. Stat. Phys. 124 (2006) 1317-1350

# Appendix A: Proof (sketch)

Proposition: The reconstruction problem is solvable iff there is a non-trivial fixed point  $\widehat{Q}^*(\eta)$ 

If reconstruction solvable: Sequence of  $\widehat{Q}^{(n)}$  converges weakly to  $\widehat{Q}^*(\eta)$  which is non-trivial.

If  $\widehat{Q}^*$  exists, non-trivial. Construct the q probabilities  $Q_x^*(\eta) = q \ \eta(x) \ \widehat{Q}^*(\eta)$ . Use them to infer some information on the root. On a leaf i, broadcast has generated symbol  $x_i$ . Generate  $\eta_i$  from  $Q_{x_i}^*$ . Given the  $\eta$ 's in generation n: generate the new  $\eta$ 's in generation n-1 from the mapping  $\eta = \mathsf{F}(\eta_1,\ldots,\eta_k)$ , down to the root. For each site j, conditional to the broadcast having produced  $X_j = x_j$ , the  $\eta_j$  provided by the above procedure is distributed according to  $Q_{x_i}^*$  (Thanks to James Martin)

## Appendix B: Variational principle 1

"Complexity" of a distribution  $\widehat{Q}$ :

$$\Sigma(\widehat{Q}) = \frac{k+1}{2} \int \widehat{W}_{e}(\eta_{1}, \eta_{2}) d\eta_{1} \widehat{Q}(\eta_{1}) d\eta_{2} \widehat{Q}(\eta_{2})$$
$$\int \widehat{W}_{v}(\eta_{1}, \dots, \eta_{k+1}) \prod_{i=1}^{k+1} d\eta_{i} \widehat{Q}(\eta_{i})$$

#### where

$$\widehat{W}_{e} \equiv -\left[\frac{\sum_{x_{1}, x_{2}} \eta_{1}(x_{1}) \eta_{2}(x_{2}) \pi(x_{1}, x_{2})}{\sum_{x_{1}, x_{2}} \overline{\eta}(x_{1}) \overline{\eta}(x_{2}) \pi(x_{1}, x_{2})}\right] \log \left[\frac{\sum_{x_{1}, x_{2}} \eta(x_{1}) \eta(x_{2}) \pi(x_{1}, x_{2})}{\sum_{x_{1}, x_{2}} \overline{\eta}(x_{1}) \overline{\eta}(x_{2}) \pi(x_{1}, x_{2})}\right]$$

$$\widehat{W}_{\mathbf{v}} \equiv -\left[\frac{\sum_{x} \prod_{i} \sum_{x_{i}} \eta_{i}(x_{i}) \pi(x, x_{i})}{\sum_{x} \prod_{i} \sum_{x_{i}} \overline{\eta}(x_{i}) \pi(x, x_{i})}\right] \log \left[\frac{\sum_{x} \prod_{i} \sum_{x_{i}} \eta_{i}(x_{i}) \pi(x, x_{i})}{\sum_{x} \prod_{i} \sum_{x_{i}} \overline{\eta}(x_{i}) \pi(x, x_{i})}\right].$$

$$\overline{\eta}(x) = 1/q$$

#### Variational principle 2

Proposition: A fixed point  $\widehat{Q}^*$  is a stationary point of  $\Sigma(Q)$ .

(Precisely: given any symmetric distribution  $\widehat{Q}$ , define

$$\Sigma^*(t) \equiv \Sigma[(1-t)\widehat{Q}^* + t\widehat{Q}].$$
 Then  $\frac{d\Sigma^*}{dt}\Big|_{t=0} = 0$ ).

Proposition In the antiferromagnetic Potts channel, if there exists a symmetric distribution  $\widehat{Q}$  such that  $\Sigma(Q) < 0$ , then the reconstruction problem is solvable.

Conjecture In any channel, if there exists a symmetric distribution  $\widehat{Q}$  such that  $\Sigma(Q)<0$ , then the reconstruction problem is solvable.

q	k	$arepsilon_{ m r}$	$arepsilon_{ ext{KS}}$		
5	2	0.2348(1)	0.2343146		
5	3	0.33881(5)	0.3381198		
5	4	0.4008(1)	0.4		
5	7	0.4986(1)	0.4976284		
5	15	0.5955(1)	0.5934409		
7	2	0.25432(5)	0.2510513		
7	4	0.43325(5)	0.4285714		
10	2	0.2716(2)	0.2636039		
15	2	0.2881(1)	0.2733670		

Table 1: Threshold for the ferromagnetic Potts channel

q	k	$arepsilon_{ m r}$	$arepsilon_{ ext{KS}}$	$arepsilon_{ ext{var}}$	$arepsilon_{ m alg}$	$arepsilon_{ ext{MP}}$	$I_*$	
5	2	0.2348(1)	0.2343146	0.23491		0.30264	0.052(5)	0
5	3	0.33881(5)	0.3381198	0.33887	0.19047	0.41712	0.06(2)	
5	$\mid 4 \mid$	0.4008(1)	0.4	0.40081	0.29046	0.48	0.06(1)	
5	7	0.4986(1)	0.4976284	0.49847	0.41114	0.57143	0.07(1)	
5	15	0.5955(1)	0.5934409	0.59422	0.53965	0.65238	0.14(1)	
7	2	0.25432(5)	0.2510513	0.25369		0.34577	0.14(1)	
7	$\mid 4 \mid$	0.43325(5)	0.4285714	0.43250	0.30769	0.53909	0.195(5)	
10	2	0.2716(2)	0.2636039	0.26977		0.38325	0.23(2)	
15	2	0.2881(1)	0.2733670	0.28472		0.41652	0.37(3)	

Table 2: Thresholds (numerical results and bounds) for the ferromagnetic Potts channel. The reconstruction threshold  $\varepsilon_{\rm r}$  satisfies the rigorous bounds  $\varepsilon_{\rm r} \geq \varepsilon_{\rm KS}$ ,  $\varepsilon_{\rm r} \geq \varepsilon_{\rm alg}$ , and  $\varepsilon_{\rm r} \leq \varepsilon_{\rm MP}^-$ . The conjectured variational principle would imply  $\varepsilon_{\rm r} \geq \varepsilon_{\rm var}$ .

q	k	$arepsilon_{ m r}$	$arepsilon_{ ext{KS}}$	$arepsilon_{ ext{var}}$	$arepsilon_{ m alg}$	$arepsilon_{ ext{MP}}^{-}$	$I_*$	
$\boxed{4}$	8	0.99953(4)				0.91552	1.56(4)	0
$\mid 4 \mid$	9	0.9908(4)	1	0.99298		0.90717	1.31(2)	0
$\mid 4 \mid$	10	0.9820(8)	0.9871708	0.98304		0.9	1.2(2)	0
$\mid 4 \mid$	11	0.9725(3)	0.9761335	0.97363	0.99736	0.89376	1.07(5)	0
$\mid 4 \mid$	12	0.9643(3)	0.9665063	0.96498	0.98946	0.88826	0.26(3)	
$\mid 4 \mid$	15	0.9431(3)	0.9436492	0.94338	0.96903	0.875	0.5(1)	0
4	18	0.9267(2)	0.9267766	0.92686	0.95264	0.86502	0.3(1)	0
5	13	0.99741(5)		0.99982		0.92308	1.76(4)	0
5	14	0.9932(1)		0.99555		0.91916	1.7(1)	0
5	15	0.9888(1)		0.99092		0.91561	1.48(5)	0
5	20	0.9685(3)	0.9788854	0.96991	0.98581	0.90177	1.1(5)	0
6	17	0.999924(5)				0.93482	2.20(4)	0.6
6	20	0.9932(3)		0.99546		0.92792	1.87(6)	$\mid 0.!$

Table 3: Antiferromagnetic, rigorous bounds:  $\varepsilon_{\rm r} \leq \varepsilon_{\rm KS}$  (KS),  $\varepsilon_{\rm r} \leq \varepsilon_{\rm alg}$  (Mossel),  $\varepsilon_{\rm r} \leq \varepsilon_{\rm var}$  (M+M),  $\varepsilon_{\rm r} \geq \varepsilon_{\rm MP}^-$  (Mossel Peres).